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5G Technology in Smart Healthcare and Smart City Development Integration with Deep Learning Architectures

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Abstract

As more and more medical devices, including as mobile phones, sensors, and remote monitoring equipment, require Internet access, wireless networks have gained considerable traction in the healthcare sector. High-performance technologies, such as the forthcoming fifth generation/sixth generation (5G/6G), are needed for data transit to and from medical equipment in order to give patients with state-of-the-art medical treatments. Furthermore, much better optimization techniques must be used when creating its primary components. Intelligent system design affects how all medical equipment operates, which presents a challenging issue in medical applications. Using information from many sources, electronic health records are built and stored there. These data are compiled in several formats and techniques. There are various big data strategies that could be utilised to reconcile the conflicting data. Artificial intelligence, machine learning and deep learning methods can be used to forecast diseases or other problems using the knowledge gathered from big data analytics. With the advent of 5G, augmented reality, virtual reality and spatial computing are all enhanced, which has a profound effect on healthcare informatics by allowing for real-time remote monitoring. With the advent of 5G technologies, healthcare services can be provided over vast distances via a vast network of interconnected devices and high-performance computation. Disease detection and treatment using dynamic data can be accomplished with the help of deep learning techniques such as Deep Convolutional Neural Networks (DCNN). Deep convolutional neural networks that incorporate images of sick regions are frequently employed for classification tasks.

Keywords: Smart Healthcare, 5G, Deep Learning

1. Introduction

Increased speed, capacity and network scalability are just a few of the features that the next 5G communication network, which will replace the present 4G network, may offer. Discussions about 5G standards, capabilities and technological vision are now taking place. The International Telecommunication Union (ITU) unveiled their "IMT-2020"-based 5G proposal in 2015. With the development of smart cities, connected objects and augmented reality, some limits have become apparent. In actuality, the 4G network is unable to satisfy the present requirements for speed, latency, communication reliability and the density of linked devices. To provide a dispersed and flexible architecture with the best performance, 5G networks have taken over [1], [2].

Real-time vital sign delivery and advanced diagnostic and therapeutic techniques are two ways that smart healthcare devices can improve the quality of healthcare. By informing patients about medical issues and potential treatments, smart health care aims to enhance their quality of life. Thanks to smart health care, patients can respond correctly in urgent situations [3]. It offers remote check-up services that reduce treatment costs and facilitates in the global growth of the services provided by medical experts. As the number of smart cities increases, a strong smart healthcare infrastructure is required to guarantee that people have access to health services.

There is no agreed-upon description of what makes up a smart city. In other cities, it could have different connotations. As a result, the idea of a "smart city" varies depending on the level of development, the desire for change and reform, the resources available and the aspirations of the local population from city to city and from country to country. A "smart city" may be defined differently in Indonesia than it is in Singapore or in City of Makassar than it is in City of Bali, for example. Even nationally, there is no consensus on what constitutes a "smart city." The definition is constantly evolving due to technological advancement. A city is a sophisticated system made up of several institutions, networks, industries and pursuits. All of these need to be connected and work well together for that city to become intelligent.

More and more scientists are becoming interested in deep learning models. They have been incorporated into a variety of applications by various researchers due to their capacity to anticipate, personalise and detect behaviour. They are also utilised in 5G networks and early results indicate promise in terms of resource allocation optimization, coordination between NFV and SDN, traffic and user mobility prediction based on user behaviour and historical data, as well as automation of challenging and time-consuming activities. Deep learning could help 5G evolve into intelligent networks that are highly adaptable for end users [2], [4].

The essay's structure is outlined below. In Section II, you will find a literature review focusing on how the 5G network can be used to provide intelligent healthcare solutions. In Section III, we will discuss the proposed methods that will be used in the 5G smart healthcare system. Standardization, objectives, and metrics for 5G smart healthcare are presented in Section IV. The final section V is the summary.

2. Literature Survey

Ullah et al. [5] An investigation of deep reinforcement learning-based UAV applications in 5G connection was part of our extensive literature review on the use of AI and ML in smart cities. They zeroed emphasis on how important the 5G connection is for UAVs in the development and upkeep of smart cities (UAVs). They described UAV positioning for throughput maximisation and data offloading, as well as mm-wave communication supported by UAVs and based on deep reinforcement learning.

A. H. Sodhro et al. [6] introduced a window-based rate control algorithm (w-RCA) to regulate the transmission rate of a source node (i.e., the window size of unacknowledged packets) and the buffer size of a destination node to improve the QoS of video transmission during telesurgery. With edge computing, a mobile network's edge server can perform cloud computing and IT services. To determine how much space will be reserved in the buffer (temporary storage) for incoming frames, a machine-learning algorithm is utilised. This has made it possible for remote video transmission in 5G networks (anywhere with internet coverage). The suggested approach maximises peak-to-mean ratio, delay, and jitter. Client and server exchange video frames via a variety of protocols (such as TCP, UDP, SDP, etc.). With the suggested fix, jitter and end-to-end video latency are reduced.

W. Chen et al. [7] proposes CcEbH to reduce congestion in severely resource-constrained networks (e.g., continuous health monitoring). The technique improves QoS by reducing network sluggishness. Since CcEbH organises the network into hierarchical levels beginning with a single node, each node in the network can be an upstream, downstream, and corresponding hierarchical level node (for example, a sink node in a wireless sensor network). Congestion occurs at a node when the rate of receiving data is greater than the rate of exiting data. Nodes upstream can examine downstream buffers (or queue size). Upstream nodes can choose a less busy downstream node. A new downstream node is chosen to gather and forward packets when a downstream node is overcrowded (for example, when buffer occupancy exceeds the upstream node's queue length by 20%). Energy is saved by CcEbH.

Paolino et al. [8] provided an adjusted 5G network design for smart cities that concentrated on virtualizing the 5G network (see Fig. 1). The original architecture attempts to combine edge computing, NFV and SDN on top of a neutral host platform, offering service providers the adaptability to modify how they deploy applications and interact with one another while also assisting infrastructure owners in managing their investment. Virtualization is necessary for a neutral platform like this since it offers infrastructure resource abstraction.

M. Chen et al. [9] offer a 5G-based Smart Diabetes system. information in real time from several sources (i.e., sensors). The data acquired by the individualised diagnosis layer is processed using modern machine learning techniques, which are based on data-accessing and data-using computer programmes. Thanks to the data sharing layer, medical professionals and patients' loved ones can share and access information about the patient's social and data environments across the 5G network. The strategy makes use of mobile devices, wearable medical technology and the upcoming 5G network (i.e., smart clothing). By the plan's primary goal is resource optimization, which will enable improved QoS for remote real-time patient monitoring. The approach consists of three tiers. The technique has demonstrated a high level of accuracy by gathering data from the sensing layer on minimising packet loss and end-to-end delay.

3. Proposed System

Artificial intelligence, machine learning and deep learning methods are used in this field to make predictions about diseases and disorders using information gathered through big data analytics [10]. 5G has a significant effect on healthcare informatics because it paves the way for real-time remote monitoring and improves augmented reality, virtual reality, and spatial computing. Healthcare services can now be provided using numerous connected devices and high-performance computation across very long distances thanks to 5G technologies. On continuously changing data, deep learning techniques like Deep Convolutional Neural Networks (DCNN) can be utilised to identify and cure disease. The suggested architecture for 5G smart healthcare is shown in Figure 1.

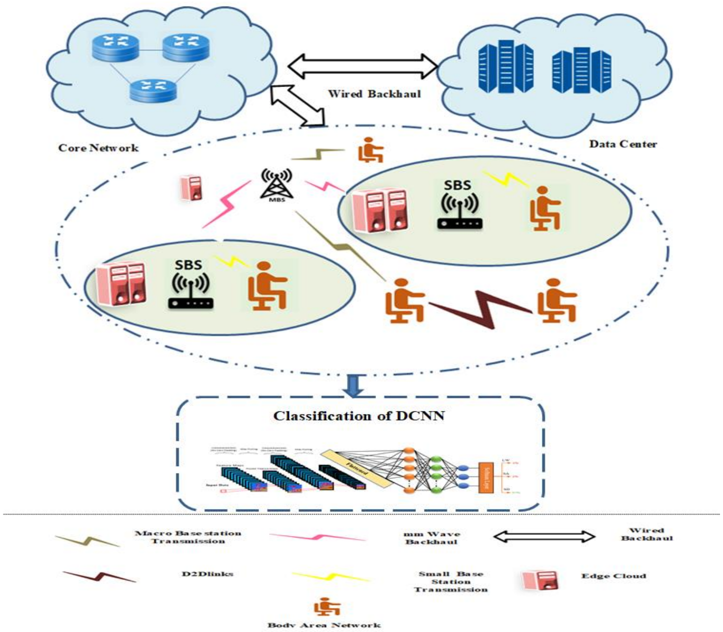

Figure 1. Architecture of Proposed 5G Smart Healthcare Diagram

3.1. 5G Structure

Small cells are radio access nodes with a constrained range and little power (a few metres to a mile). The various kinds of small cells are very useful for numerous 5G smart healthcare applications. Since smart healthcare applications require high data rates (for instance, remote surgery required data rates between 137 Mbps and 1.6 Gbps), small cells are one possibility [12]. Femto, pico and microcells are the three sizes of tiny cells, which range from smaller to larger. In contrast to the macro cell, which has a range of around 20 miles, these are referred to as small cells. Femtocells are used to expand capacity and coverage in a constrained area, such as a house, a hospital, or another building. That can accommodate 30 users at 0.1 kilometres. Picocells have a larger capacity and coverage, allowing them to accommodate up to 100 users across an area of 1 km. In order to increase wireless and cellular coverage in a small space, picocells are frequently utilised. The main distinctions between a microcell and a picocell, even though it can be challenging to do so, are the coverage area and user support. Microcells can accommodate up to 2000 people in a 2-kilometre area. The cellular network makes use of macro cells to provide radio coverage for a variety of mobile network access. It offers good output effectiveness and coverage [13]. On stations with high output power often in the tens of watts range a microcell is deployed. More than 2000 people can use it within a 30-kilometer range.

The network can recycle higher frequencies by using micro cells to boost area spectrum efficiency. While the user plane manages data transfer in micro cells, where the two planes also operate independently, the control plane provides communication and movement [14]. This means that the UE needs to be linked to both the macro-cell and the small-cell base stations at the same time. Small-cell base stations employ higher frequencies to facilitate high-capacity data transfer, while macro-cell base stations use lower frequency bands to promote connectivity and mobility (control plane). There are four different sizes of base stations in a heterogeneous network: macro, micro, Pico and Femto (HetNets). Incorporating them allows for greater spectrum use and the provision of various forms of coverage. [15]

3.2. Characteristics and Supporting Technologies for 5G

Connecting two networked devices directly, without going through a base station (BS) or a core network, is called device-to-device communication (D2D). D2D communications can aid in problem-solving in extremely dense networks [16], [17]. To share their radio access link or to exchange information, each terminal in a D2D connection can speak with the others directly. D2D communication, especially in unlicensed frequency ranges, can reduce interference. D2D communication is not a notion in the 4G network. All communications are routed through the gateway and base station. Routing that is inefficient, particularly when devices are close to one another. When more than one machine is involved, it makes more sense for them to communicate directly with one another. Bluetooth and WLAN ad hoc mode are just two examples of the technologies that allow devices to connect with one another in the unlicensed spectrum outside of cellular networks [18] However, these interactions might be impacted by noise. However, licenced spectrum ensures the quality of services if the link is adequately maintained. Base stations must disregard intra-cell interference for these D2D communications to work [19]. Millimetre-wave transmission (mmWaves) The mmWaves spectrum spans the frequencies of 20 GHz and 300 GHz. Since there is a scarcity of spectrum below 3GHz, 5G must boost its frequency to take advantage of the mmWaves band's abundant unused capacity, which is primarily between 20 GHz and 90 GHz. Multiple uses, including smart healthcare, could benefit from the potential elimination of the route loss problem brought on using tiny cells and mmWaves. There is a wide variety of cutting-edge uses for mmWaves now that they are both inexpensive and practical. The finest part is that mmWave frees lower frequencies from their load and broadens wireless communication beyond radio technology's limitations [19]-[24].

(1) Software-defined network, first (SDN): High bandwidth is a requirement for many applications and SDN is an architecture that actively, manageably, adaptably, and inexpensively offers it. SDN can handle contemporary data centers, virtualized servers and storage architecture while also enhancing the flexibility and agility of the network. SDN networking specifies steps for building, configuring, and maintaining networks by dividing them into separate control and forwarding planes. SDN can enable a variety of 5G smart healthcare requirements. Depending on operator

policies, some use cases are handled in the cloud, while those requiring a quick response and virtual services are handled on the edge cloud.

(2) The Virtualization of Network Functions Network utilities written in software and deployed as virtual machines on regular servers eliminate the need for costly specialized hardware like firewalls and route RS. This is possible thanks to the emerging networking technique known as (NFV). D2D connectivity is necessary for smart healthcare and 5G must make it possible. There will surely be a ton of data generated as a result. All the generated data is too much for the centralized data center to handle. Informed decisions must be taken for the management of data at edge clouds and cloud servers. Based on QoS requirements, data can be transferred into the network via NFV. This is necessary to guarantee the network's scalability and adaptability.

(3) Edge processing: Edge computing, a distributed technology design, locates data processing at the network's edge, near to the data's original source. Machines are anticipated to make decisions and take actions that are consistent with the mission in the future of intelligent healthcare. The reactions and conclusions that machines offer require processed data. Real-time processed data is crucial in many situations. In these circumstances, where decision time is increasingly crucial, edge computing is crucial, especially in 5G-based networks.

3.3. Classification of DCNN

Here, we cover CNN and the studies that employed CNN to set the stage for the construction of the 5G wireless mobile network [15], [24]. To recognise patterns and analyse images, many people turn to the feed-forward neural network known as a convolutional neural network (CNN). It stands out from the crowd because to its user-friendliness, flexibility, and limited availability of training sites. Layers like as input, convolution, pooling, and output make up just some of a CNN's complex architecture. Before doing any actual convolutions, the convolution layer uses a filter to extract a feature map from the input image. Down sampled feature maps are sent from the convolution layer to the pooling layer. To create a single pixel, n neighbouring pixels' bias (bp + 1), scalar weight (Wp + 1) and activation function are added together. Because of this, the resulting feature map is somewhat simplistic. CNN can practise concurrently, which greatly boosts the effectiveness of the network. It once again increased resilience and scaling was made possible by using the subsampling method. These equations can be used to explain how CNN processes output at its various levels:

$$O_{p,q}^{(l,k)} = \tanh\left(\sum_{t=0}^{f-1}\sum_{r=0}^{K_h}\sum_{c=0}^{K_w} W_{(r,c)}^{(k,t)} O_{(p+r,p+c)}^{(l-1,t)} + Bias^{(x,k)}\right) \tag{1}$$

An O(l,k) p,q representation of a neuron's output at layer l, feature pattern k, row p and column q, where f is the number of convolution cores in the feature pattern. For the kth feature pattern, row p and column q, the neuron's output is described as follows during the subsampling stage:

$$O_{p,q}^{(l,k)} = \tanh\left(\sum_{t=0}^{f-1}\sum_{r=0}^{K_h}\sum_{c=0}^{K_w} W_{(r,c)}^{(k,t)} O_{(p+r,p+c)}^{(l-1,t)} + Bias^{(x,k)}\right) \tag{2}$$

The xth hidden layer H displays the following as neuron j's output:

$$O_{(l,y)} = \tanh\left(\sum_{k=0}^{s-1}\sum_{p=0}^{S_h}\sum_{q=0}^{S_w} W_{(p,q)}^{(y,k)} O_{(p,q)}^{(l-1,t)} + Bias^{(x,y)}\right) \tag{3}$$

The feature pattern subset employed in the subsampling layer is denoted by s. In the xth output layer, neuron I has an output that is provided by the equation:

$$O_{p,q}^{(l,k)} = \tanh\left(\sum_{y=0}^{H} o_{(l-=1,y)} W_{(x,y)}^{l} + Bias^{(x,k)}\right) \tag{4}$$

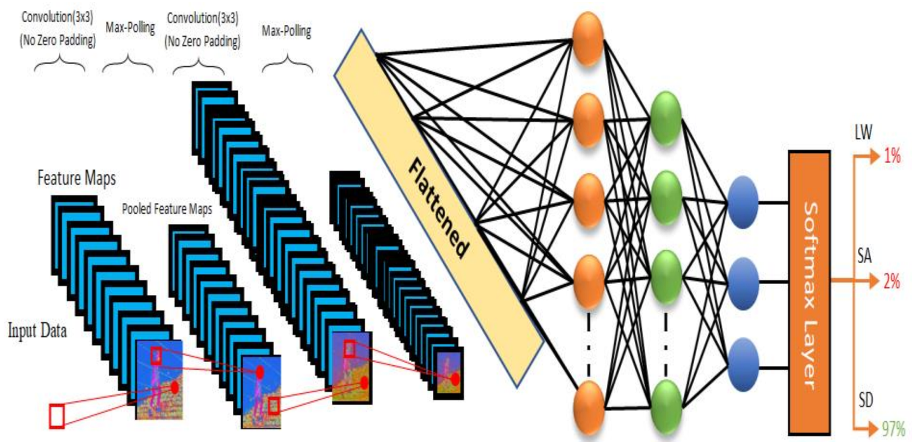

Figure 2. Architecture of DCNN

CNN is a subset of the broader family of feed-forward ANNs; in contrast to fully connected ANNs, in which all neurons in each layer are connected to all neurons in the layer below it, its constituent neurons are only interconnected with one another locally. The visual cortex of the human brain served as inspiration for this design. For a CNN, the major processing step is a convolution of the filters with a given input image, where the filters themselves are represented by a series of arbitrary initialised connections that form the local connection. The structure is made up of many features extraction levels. Convolution, non-linear neuron activation and feature pooling are the three primary building blocks of each stage. A deep convolutional neural network (CNN) is depicted in its most fundamental form in Figure 2. When many successive steps of feature extraction are linked together in a CNN, we say that the CNN is deep.

4. Result and Discussion

4.1. Experimental Setup

5G network and Its requirements as follows: Broadband improvements for mobile devices; Massively parallel machine communications; High-reliability, low-latency communications; and WRAN (Wireless Regional Area Networks) [24].

4.2. Performance Metrics

1. PDR (Packet Delivery Ratio)

Table 1. Packet Delivery Ratio for DCNN Method with Existing System

No of Nodes	CCRT	(w-RCA)	(HOCA)	(CcEbH)	DCNN
20	82.24	84.17	87.23	89.86	92.45
40	82.62	84.37	88.37	89.77	93.65
60	82.93	85.48	87.59	89.25	92.98
80	83.11	85.65	87.91	90.17	94.28
100	83.58	85.98	88.23	91.75	95.85

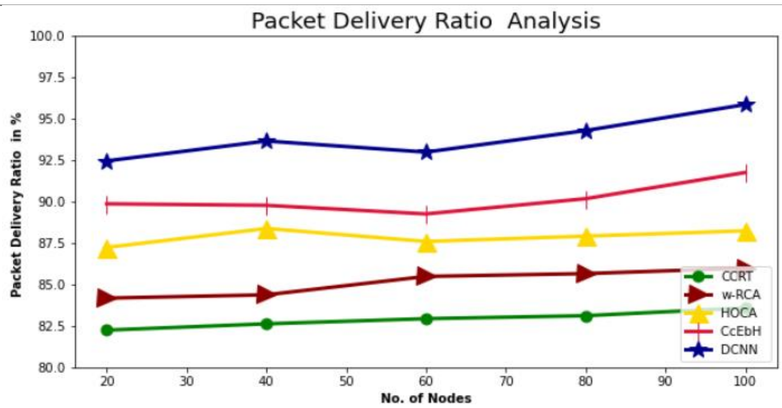

Figure 3. Packet Delivery Ratio of DCNN Method with Existing System

When individuals talk about the "package Delivery ratio," they are referring to the ratio of the total quantity of packages that were sent from the sender node to the total quantity of packages that were received at the destination. Fig 3 presents packet delivery ratio analysis DCNN method with existing system like CCRT, w-RCA, HOCA and CcEbH. For 20 nodes, it is 92.45% of PDR for the DCNN method, while the previous procedures such as CCRT, w-RCA, HOCA and CcEbH processes have achieved a PDR of 82.24%, 84.17%, 87.23% and 89.86% respectively. On the other hand, when compared to the presentations of the other methods, the DCNN process yields better outcomes. Similarly, the PDR of the suggested technique is 95.85% with 100 nodes while that of the other current methods ranges from 83.58% to 91.75%.

2. Packet loss Ratio (PLR)

Table 2. Packet Loss Ratio for DCNN Method with Existing System

No of Nodes	(CCRT)	(w-RCA)	(HOCA)	(CcEbH)	DCNN
20	38.16	36.54	34.58	33.06	32.14
40	38.27	36.84	35.27	33.56	32.47
60	39.65	37.12	35.54	33.72	32.87
80	38.36	37.37	36.25	33.95	32.64
100	39.26	37.72	35.94	34.12	33.15

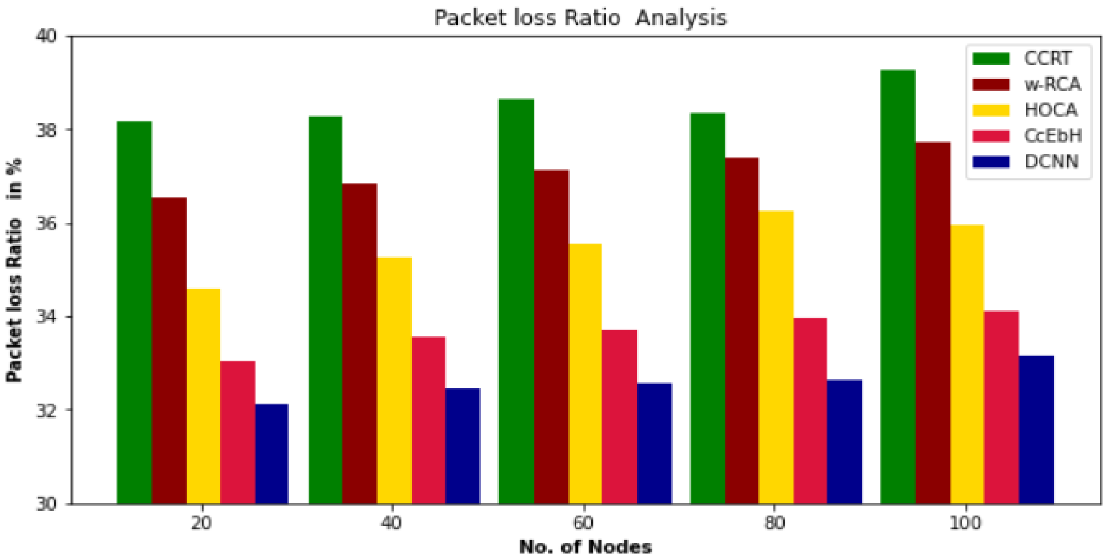

Figure 4. Packet Loss Ratio of DCNN Method with Existing System

Tab.2 and Fig.4 explain the packet loss ratio analysis of the DCNN method with other existing techniques. The data clearly explains that the proposed method has the least PLR compared to the other methods in all aspects. For example, with 20 nodes, the proposed method has a PLR of 32.14%, while it is 38.16%, 36.54%, 34.58% and 33.06% for CCRT, w-RCA, HOCA and CcEbH, respectively. The DCNN method has greater performance with less PLR. Similarly, with 100 nodes, the proposed method has 33.15% of PLR whereas the methods for CCRT, w-RCA, HOCA and CcEbH have PLR of 39.26%, 37.72%, 35.94% and 34.12%, respectively.

3. Throughput

Table 3. Throughput Analysis for DCNN Method with Existing System

No of Nodes	(CCRT)	(w-RCA)	(HOCA)	(CcEbH)	DCNN
100	721.56	815.26	895.34	984.25	1194.25
200	734.11	834.16	905.26	1021.26	1218.35
300	785.26	858.76	915.26	1135.54	1225.14

400	791.04	861.24	938.14	1146.81	1234.25
500	804.35	876.35	956.24	1167.28	1256.76

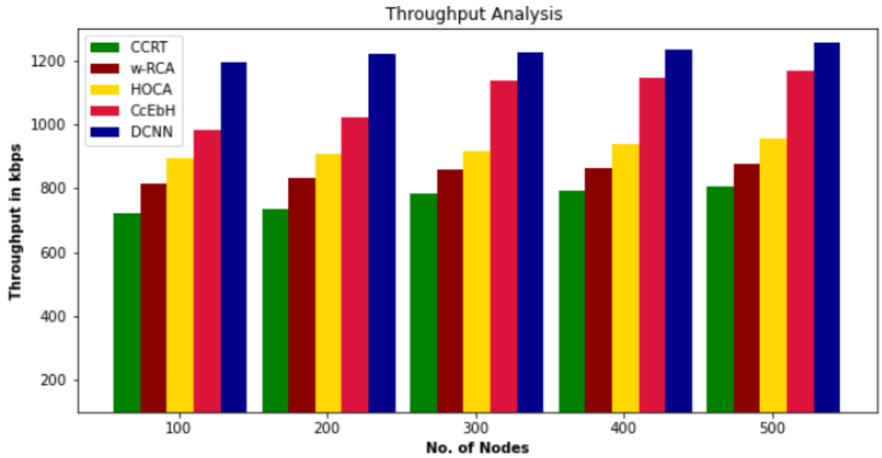

Figure 5. Throughput Analysis for DCNN Method with Existing System

The data clearly demonstrates that the proposed method surpasses the other techniques in all aspects. The throughput study of the DCNN methodology in comparison to the present methods is described in Tab.3 and Fig.5 For example, with 100 data points, the DCNN method has a throughput of 1194.25 kbps while the other existing methods like CCRT, w-RCA, HOCA and CcEbH have a throughput of 721.56 kbps, 815.26 kbps, 895.34 kbps and 984.25 kbps, respectively. Similarly, with 500 data points, the proposed method has 1256.76 kbps of throughput while the other existing methods, CCRT, w-RCA, HOCA and CcEbH have a throughput of 804.35 kbps, 876.35 kbps, 956.24 kbps and 1167.28 kbps, respectively. This proves that the DCNN technique has higher performance with greater throughput.

4. Sensitivity Analysis

Table 4. Sensitivity Analysis of DCNN Method with Existing System

No of Nodes	(CCRT)	(w-RCA)	(HOCA)	(CcEbH)	DCNN
100	66.93	71.51	76.84	82.39	88.32
200	68.21	73.84	78.39	83.56	90.47
300	69.37	75.31	79.21	84.29	91.48
400	70.27	74.85	80.49	84.94	92.54
500	70.84	75.93	81.05	85.36	93.63

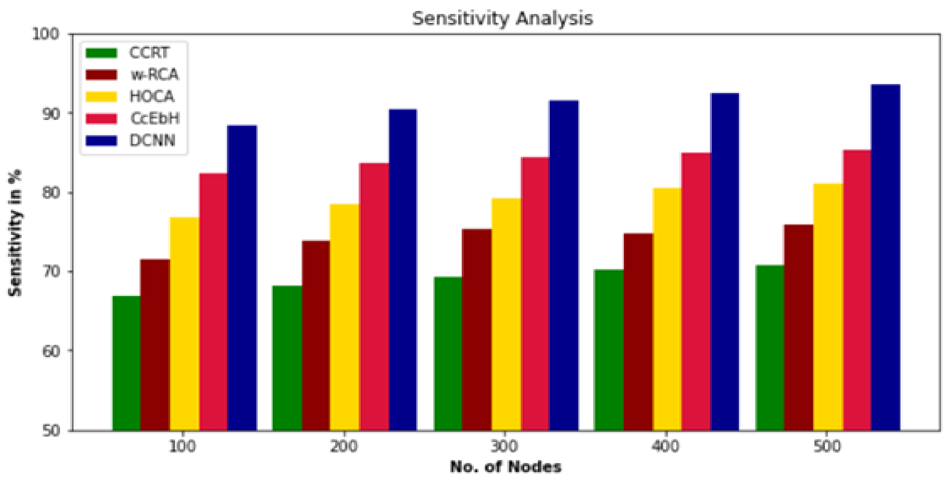

Figure 6. Sensitivity Analysis for DCNN Method with Existing System

Fig. 6 and Tab. 4 illustrate a comparative Sensitivity examination of the DCNN approach with other existing methods. The figure shows that the deep learning approach has resulted in higher performance with Sensitivity. For example, with 100 number of nodes, the Sensitivity value is 88.32% for DCNN, whereas the CCRT, w-RCA, HOCA and CcEbH models have obtained Sensitivity of 66.93%, 71.51%, 76.84%, and 82.39%, respectively. However, the DCNN model has shown maximum performance with different node size. Similarly, under 500 nodes, the Sensitivity value of DCNN is 93.63%, while it is 70.84%, 75.93%, 81.05% and 85.36% for CCRT, w-RCA, HOCA and CcEbH models, respectively.

5. Specificity Analysis

Table 5. Specificity Analysis for DCNN Method with Existing System

No of Nodes	(CCRT)	(w-RCA)	(HOCA)	(CcEbH)	DCNN
100	68.92	73.57	80.59	88.32	93.74
200	69.57	75.49	83.27	89.40	94.26
300	70.18	76.83	82.95	90.37	94.95
400	72.94	77.95	84.64	91.85	95.32
500	73.28	78.36	85.78	92.64	96.04

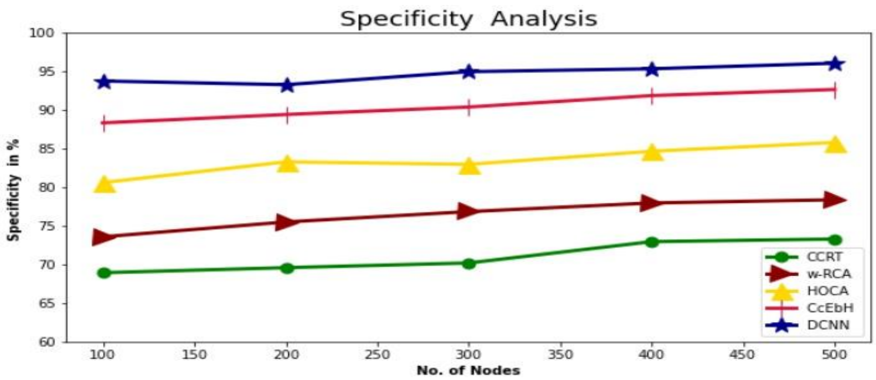

Figure 7. Specificity Analysis for DCNN Method with Existing System

Fig. 7 and Tab. 5 illustrate a comparative Specificity examination of the DCNN approach with other existing methods. The figure shows that the deep learning approach has resulted in higher performance with Specificity. For example, with 100 number of nodes, the Specificity value is 93.74% for DCNN, whereas the CCRT, w-RCA, HOCA and CcEbH models have obtained slightly enhanced Specificity of 68.92%, 73.57%, 80.59%, and 88.32%, respectively. However, the DCNN model has shown maximum performance with different node size. Similarly, under 500 nodes, the Specificity value of DCNN is 96.04%, while it is 73.28%, 78.36%, 85.78% and 92.64% for CCRT, w-RCA, HOCA and CcEbH models, respectively.

5. Conclusion

In this paper, we examined prior studies on the networking aspect of 5G for smart healthcare and talked about potential future research topics Offering cutting-edge medical care to patients requires the use of high-performance technologies, such as the upcoming fifth generation/sixth generation (5G/6G), for data transit to and from medical equipment. More than that, cutting-edge optimization strategies must be incorporated into the design and construction of its core elements. The complexity of intelligent system design in medical applications stems from the fact that it affects the performance of every piece of medical machinery. There, electronic health records (EHRs) are constructed and updated using data from numerous sources. It uses a wide range of tools and file types to compile these statistics. The differences could be resolved using any number of big data techniques. Transmitting data to and from medical devices requires high-performance technologies like the fifth and sixth generations (5G/6G) to provide patients with cutting-edge care. In addition, cutting-edge optimization strategies must be utilised during the development of its primary parts. Since intelligent system design affects the performance of all medical equipment, it presents unique challenges in medical settings. Finally, we briefly discussed the difficulties and problems that a future 5G smart healthcare system would have to deal with. The proposed healthcare model has enhanced several potential future outcomes, some of which are included here. In Other algorithms, like KNN or fuzzy systems, may be used with the recommended technique; In the future, the selection algorithm might be used for optimization and fruitful results; and the recommended approach might be strengthened to accommodate a variety of patients by including their profiles; and also In the future, PSO (Particle Swarm Optimization) will be used as the feature selection method, which will enhance system optimization and better display the system.

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Authors' Contributions

The authors contributed toward data analysis, drafting, and revising the paper and agreed to be responsible for all the aspects of this work.

Declaration Of Conflicts of Interests

Authors declare that they have no conflict of interest.

Consent For Publication

The authors read and aware of publishing the manuscript in International Journal of Communication Networks and Information Security

Declarations

Authors declares that all works are original and this manuscript has not been published in any journal.

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